# AN IOT BASED SMART ARTIFICIAL PANCREAS FOR TREATING DIABETES

**A SYNOPSIS**

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# 1 Introduction

The thesis will focus on geriatric type 2 diabetes (T2D), a challenging problem. Foremost, T2D is characterized by deficient or inefficient insulin. This is a departure from Type 1 diabetes (T1D) where insulin secretion is completely absent. Consequently, interventions are required to handle the insulin's insufficiency and/or inefficiency. Besides, interactions between endogenous insulin and interventions (exogenous insulin or oral hypoglycemic agents a.k.a. OHA) are difficult to comprehend. This is general makes T2D a challenging problem. However, it accentuates in elderly people due to: co-morbidity, multiple drug intake, hormonal changes, activity variations, food influences, and others. Further, the insulin sensitivity reduces with age, a major factor for diabetes in India. These geriatric factors makes the blood glucose levels quite brittle, i.e., frequent hyper and hypo events. This adds a very complex dimension to an already challenging problem of managing T2D.

In India and other low-and-middle income countries, T2D is wide-spread with over 370 Mn people with diabetes and 180 Mn susceptible to it in the next decade. This is mainly attributed to food and lifestyle. Further, T2D in these countries picks up with age. Therefore, managing geriatric T2D is pivotal as blood glucose excursions could lead to hyper and hypo conditions that affect independence, life quality and could be even fatal at times. Albeit these challenges, understanding food influences and activity levels both at population and individual levels presents a stiff challenge. While macro understanding about food such as low carbohydrate intake are well recognized, exact macronutrient range recommendations for remission, reversal and progression of diabetes is lacking to our best knowledge for Indian population. Similarly, managing geriatric T2D requires personalization wherein fusing knowledge of food influences and activity levels with insulin infusion becomes paramount. This demands a renewed approach wherein recent technological advances, tools, and data starting from population to individual levels are required. Further, management tools are suited only for people with T2D and a holistic digital tool requires recommendations for normal glucose tolerance (NGT) or pre-diabetes (PD) patients. Whereas, management is possible for geriatric patients who are new diagnosed to ones with certain threshold of insulin resistance post which the E-T2D patient behaves as T1D. In this phase, the patient can have dietary compliance and management is through full automation. Therefore, a typical T2D digital tool should have a recomender for nutrients for NGT and PD patients, management tool for E-T2D, and management plus compliance tool for E-T2D with no insulin tolerance. This thesis addresses these gaps by:

*(i)* Understand food influences from data-sets at both population and individual levels;

*(ii)* Derive recommendations at population levels to reverse, remission and prevention of T2D.

*(iii)* Develop a Human Digital Twin (HDT) for managing T2D that combines predictive control with time-series forecasting, explainable artificial intelligence (XAI), food nutrient estimation and other tools to compute optimal insulin infusion for managing geriatric T2D. This leads to a learning-based model predictive controller.

*(iv)* Develop an individualized adaptive patient model to capture complex nonlinear dynamics using a simple model.

*(v)* Demonstrate the LB-MPC on 15 human patient models for managing geriatric T2D.

*(vi)* Cross-fertilize macronutrient recommendations on individual geriatric T2D patients to verify the gains in terms of T2D management.

# 2 Literature Review

Diabetes is prevalent in India, majority of the patients have T2D. Mohan et al. [1] illustrate the role of unhealthy diet towards rapid rise of T2D in India. The diet with insufficient protein, fiber, fat and excess of carbohydrates will lead to the development of T2D. Proper and balanced macronutrient (carbohydrate, fat, protein, and fiber) recommendation tool helps to prevent the development and progression of T2D, also it can induce remission of T2D at population level (see, Magkos et al. [2] and references therein). Proper and healthy diet helps at individual levels to manage T2D and connotations of these towards population message is quite evident.

The diet's effect on blood glucose level (BGL) vaires among individuals due to food preparation and patient dynamics. Papakonstantinou et al. [3] showed that controlling the postprandial BGL is challenging and results in complications due to prolonged hyperglycemia. Estimating the food nutrients and nutrient absorption on individuals will become important in effective diabetes management. Churuang et al. [4] studied the effect of low and reduced carbohydrate on T2D. The study shows that healthy diet and its patterns leads to effective diabetes management and insulin dosage could be minimized to maintain the BGL with in a target range. Over time, patients with T2D on multiple oral therapies and geriatric conditions become similar to T1D patients requiring exogenous insulin infusion (see, William et al. [5]). OHA and conventional insulin therapy (multiple daily insulin injections) will have multiple challenges may not suffice for such patients leading to frequent hyper and hypo events.

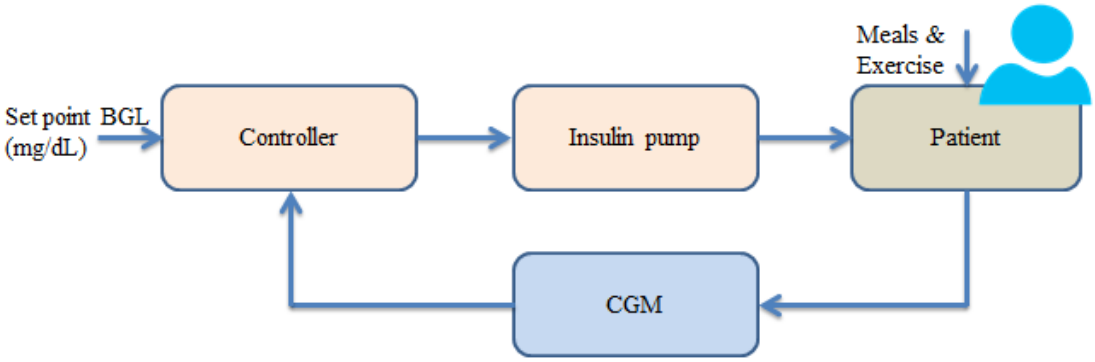


**Figure 1:** Artificial Pancreas System

Personalized artificial pancreas (AP) automates the insulin infusion to manage BGL in T2D patients. Figure 1 shows AP's block diagram having: mathematical control algorithm having patient model that uses the real time blood glucose measurements from continuous glucose sensors to compute the insulin dosage was discussed in Leon et al. [6]. Existing control algorithm for AP can be broadly discerned to be: reactive and predictive reviewed by Kovatchev. [7]. Reactive control algorithm computes insulin dosing based on the current glucose measurements. Widely used reactive controllers are proportional integral derivative controller (PID), fuzzy and other techniques relying on measurements was reported by alshalalfah et al. [8], pintaudi et al. [9], Yan et al. [10]. The review about insulin pump were presented in Sora et al. [11]. The Medtronic 722 insulin pump uses the PID controller with features such as automatic insulin shut-off, i.e., when BGL reaches closer to the lower target value and patient can manually insert the meal announcements to plan the insulin infusion.

Still these actions are based on measurements without including patient-specific data lacking personalization. Predictive control methods use the mathematical model and patient-specific data to compute the insulin infusion to overcome the shortcomings was discussed by Kang et al. [12]. Keshary et al. [13] designed a MPC to recommend the optimal insulin infusion by using multimedia data. MPC has emerged as a promising solution that uses patient physiological model to compute optimal insulin infusion. It solves multi-time step optimization routine by embedding recent measurements (e.g., BGL) with the patient model to compute optimal insulin infusion. Personalized MPC's efficacy has been studied and demonstrated in recent studies by Ekhlaspour et al. [14]. Recently, MPC development has attracted significant attention due to its ability to personalize the insulin infusion. Nevertheless, MPC design is overwhelming as model parameters need to be estimated that requires clinical measurements (e.g., plasma insulin). Cobry et al. [15] reviewed the existing available insulin pumps. Ominipod5 and t:slim X2 Control IQ are two insulin pumps with MPC that are approved by FDA available in the market. The studies prove that these pumps can increase the time in range

(TIR) of a T1D patient. Personalized AP for T1D with validation trials up to 6 months on individual patient was reported by Toffanin et al. [16] and several long period trails are also reported by Abraham et al. [17]. MPC control for guiding long acting insulin based on fasting glucose for T2D is presented in Aradottir at al. [18].

However designing an MPC for T2D is limited due to internal insulin secretion form pancreas, complex patient models (e.g, nonlinear), model parameter estimation and optimization routines. This leads to several challenges to personalization, poor understanding of food influences and their variabilities, effect of geriatric conditions on BGL and technical challenges such as ignoring delays in subcutaneous sensing and actuation during MPC was studied by Sun et al. [19]. Personalization is the key factor for effective diabetes management especially in elderly T2D patients, so recent research is more focused towards personalizing the control algorithms that capture certain aspects (e.g., insulin-glucose interaction and food influences on BGL). The second challenge for fully automated AP system is, currently available AP doesn't estimate the carbohydrate (CHO) content of a food. The patient needs to manually enter the CHO content present in their food (see Rodriquez et al. [20]). This is especially burdensome on users and caregivers because inaccurate assessment of CHO will lead to inaccurate bolus estimation and it can induce hypoglycemia (BGL value less than 70 $\mathrm{mg/dL}$) or prolong hyperglycemia (BGL above 180 $\mathrm{mg/dL}$). Hettarachchi et al. [21] have reported the large insulin dosage error rate due to inaccurate CHO values.

A framework that can capture the patient physiological dynamics with personalized model, IoMT architecture to collect patients' data, and can incorporate the influence of food on BGL will be the great choice for developing the personalized AP. Human digital twin (HDT) for personalized healthcare was reviewed by Okegbile et al. [22]. It is the advanced technology has the ability to personalize the treatment methods. However, the role of HDT in personalizing T2D treatments backed by clinical data, macronutrient recommendations at poulation level, patient's contextual data, and other such data.

# 3 Objectives

Our objective in the thesis are:

1. An IoT-based AP that has two degrees of control: insulin infusion and life-style (food intake) for managing E-T2D.
2. A recommender that uses a data-driven optimization to provide macronutrient recommendations for normal glucose tolerence (NGT), pre diabetes (PD), and newly diagnosed diabetes (NDD) patients for diabetes prevention of progression,

remission, and diabetes reversal, respectively. The recommender uses the population level data for providing the recommendations.

3. A HDT for personalized E-T2D management having three major components: physical twin (PT), digital twin (DT), and interfaces. The digital twin has: modules for data aggregation, suite of models to provide intelligence, an adaptive patient model, interfaces to connect PT and DT.

4. An IoMT architecture to aggregate data vis-á-vis HDT for E-T2D management.

5. A learning-based model predictive controller (LB-MPC) that uses a patient model and embeds intelligence aggregated from data to personalize insulin infusion based on specific patient conditions.

6. Study the role of macronutrient recommendations from population level data and its implications on personalization to study the insulin infusion changes for patients with the food recommendations compliance.

7. Study the role of macronutrient recommendations through Indian Council for Medical Research-India Diabetes (ICMR-INDIAB) data collected across India to provide population level recommendations.

8. Illustrate HDT capabilities to manage T2D through clinical studies conducted on 15 patients for 14 days combining contextual and patient specific data.

# 4 Research Problem

This section summarizes the research work. The research focuses on geriatric T2D from population level to individualized management. First, the research studies the food influences and the ability to remit and prevention of progression of diabetes through macronutrient recommendations. Second, the role of HDT towards personalized E-T2D management is studied. The idea is to create a digital replica that mimics an actual patient condition and builds intelligence through suite of models that use the data aggregated from IoMT devices. The HDT has the components for data aggregation, suite of models to build intelligence, and interfaces between virtual and digital twin. Third, the research focuses on fusing macronutrient recommendations with blood glucose management by studying the compliance of the macronutrient recommendations for patients with T2D. Finally, the role of compliance for T1D patients on macronutrient recommendations is studied. This is particularly important for E-T2D patients whose insulin resistance increases with diabetes age. In what follows, a succinct description of the research outcomes are presented.

## 4.1 Macronutrient Recommendation for Remission and Progression of Diabetes in Asian Indians

As explained earlier, for NGT and PD patients insulin or OHA treatments are not recommended. Therefore, prevention to progression and remission are important in these categories. In the absence of medical interventions, life-style involving food intake and activity levels could be modified to treat T2D. In our study, food influences are considered as they are more pronounced in E-T2D. Nutrient absorption varies among individuals and even within a particular patient. Therefore, macronutrient recommendations are studied for three categories through a data-driven optimization approach. The recommender uses the population level data collected as part of the ICMR-INDIAB study to propose macronutrient recommendations for all three categories of the T2D patients. In essence, the data is used to generate models for NGT, PD, and NDD patients. Then the macronutrient percentage consumption is computed as an optimization variable. A data-driven optimization approach was used in which the inputs are: anthropometric data, domicile, and other patient specific data. Outcomes are the macronutrient recommendations in terms of carbohydrate, proteins, fats, and fiber. The patient data were collected from across 30 states/union territories (UT) of India.

### 4.1.1 Optimization-Driven Macronutrinet Recommendations

The optimization workflow and methodology used to estimate the macronutrient recommendation is shown in Figure 2.

A linear regression model capturing the influences of covariates on $HbA1c\ \%$ was developed using an optimization routine. In $HbA1c\ \%$ equation the dietary covariates (macronutrients - carbohydrate, protein, fat, and fibre) were taken as optimization variables and other non dietary covariates were fixed. The $HbA1c$ was estimated by the following linear regression equation.

$$HbA1c_{est} = A \times X + B \times Z \tag{1}$$

where $X$ models the vector of nondietary covariates such as age, sex, and activity levels etc, and selected dietary factors (other than macronutrients). The coefficient $A$ was computed by linear regression model. Here, $Z$ models the macronutrients and $B$ is their linear regression coefficients. The optimization problem was solved to recommend the optimal macronutrients. The objective of this is reducing the error between estimated HbA1c and the target. Target HbA1c was fixed depending on the glycemic category. The recommendations were compliance requirements for ICMR and has re-

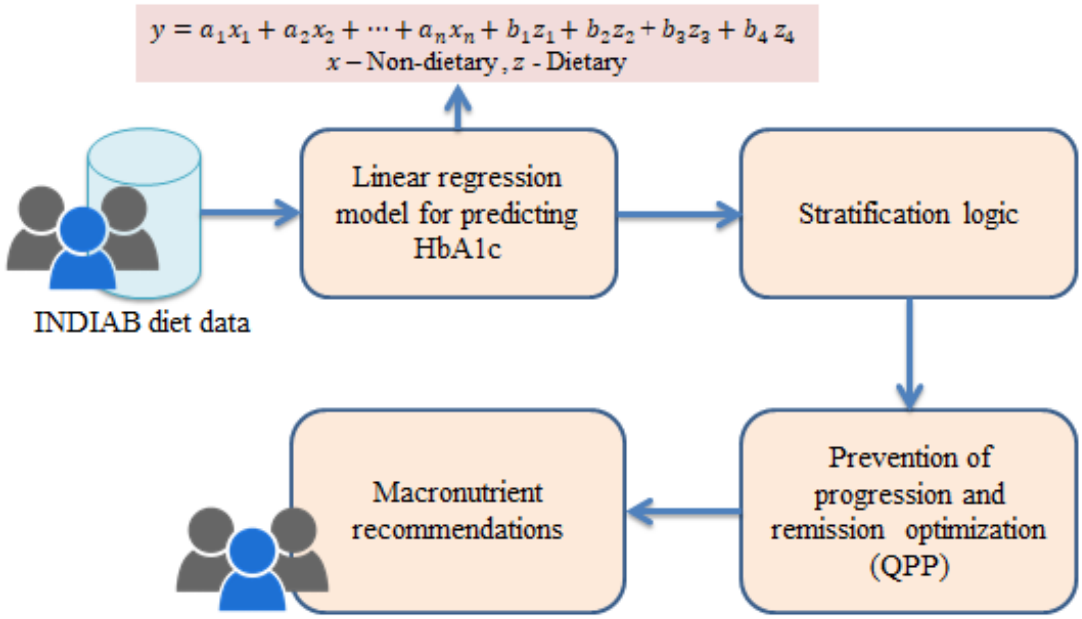
$y = a_1x_1 + a_2x_2 + \cdots + a_nx_n + b_1z_1 + b_2z_2 + b_3z_3 + b_4z_4$
$x$ – Non-dietary, $z$ - Dietary
INDIAB diet data
Linear regression model for predicting HbA1c
Stratification logic
Prevention of progression and remission optimization (QPP)
Macronutrient recommendations

**Figure 2:** Optimization workflow

ceived considerable media attention.

## 4.2 HDT Framework for Effective Diabetes Management

Main idea to build HDT is to mimic the actual patient by aggregating patient's contextual data, clinical measurements, and other data. Suite of models are used to model different aspects of the patient such as time-series blood glucose measurements, insulin, food intake, activity, and other data. The HDT uses an IoMT architecture to collect patient data. It has the personalized patient model to capture specific aspects of the patient. As shown in Figure 3 it has three basic entities: patient, virtual twin, and interfaces.

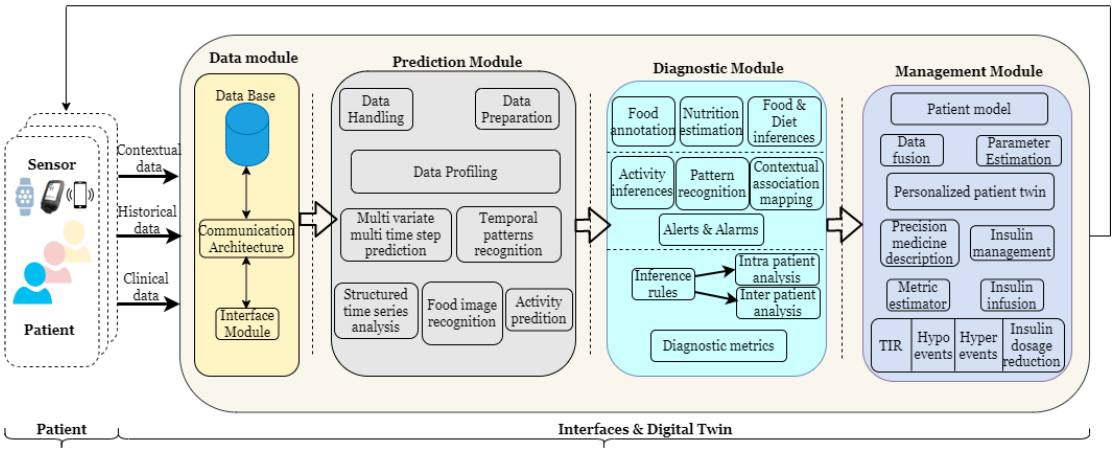


**Figure 3:** HDT Architecture

The patient data were collected at Jothydev's Diabetes Research Center (JDRC), Trivandrum, Kerala. The data module in HDT has IoT devices and sensors to collect the data. Using IoMT architecture patients' vital signs data, blood glucose level, food data, activity and other sensed information are collected. Prediction module provides future predictions by using the sensed information and historical information from data module. Diagnostic module uses the multiple tools to obtain various insights about patient data from data module and information form prediction module. The management module is responsible for making suitable recommendations about insulin dosage based on the information form data module, prediction module and diagnostic module. The modules in HDT framework helps to personalize the insulin infusion, food recommendations, activity levels, and other aspects.

## 4.3 Adaptive Personalized Patient Model

The patient physiological model available in literature are very complex and requires clinical measurements (e.g., plasma insulin) to estimate the model parameters whose computations are cumbersome. To overcome this an adaptive patient model that personalize insulin infusion based on geriatric factors was proposed. This model uses the adaptive parameter estimation algorithm to estimate the model parameters. The model is simple and agile to adapt its parameter depending on patient conditions. The personal glucose dynamics as,

$$G(k+1) = \zeta_1(k)G(k) + \zeta_2(k)I(k) + \zeta_3(k)CHO(k) \tag{2}$$

The modeling (2) is a simplified version of the nonlinear patient dynamics. The model parameters $\zeta_1,\ \zeta_2, and\ \zeta_3$ needs to be recursively updated using current measurements. It uses the recursive parameter estimation technique with exponential forgetting for computing the model parameters. The patient model with insulin and food dynamics is represented in a compact form as:

$$G(k+1) = H(k)w(k) + \varepsilon \tag{3}$$

where $\varepsilon$ is assumed to be normally distributed bounded additive noise with $\|\varepsilon(k)\|_2 \leq \alpha$ with $\alpha \in \mathcal{R}^+$.

$$H(k) = [G(k)\ I(k)\ CHO(k)]$$

$$w(k) = [\zeta_1\ \zeta_2\ \zeta_3]^T$$

In the recursive model parameter estimation, during each time instant $k$, the optimization problem in (4) is solved to identify the parameter with forgetting factor $\lambda$. Note that the forgetting factor might be adjusted for each patient.

$$\begin{aligned} \min_{w(k)} \sum_{k=0}^{N_P} \lambda^{N_P-k}[(G(k+1) - H(k)w(k))^T \Pi(k)(G(k+1) \\ - H(k)w(k)] \\ \text{s.t.} \quad \Pi(k) \in \mathcal{R}^+ \end{aligned} \tag{4}$$

Algorithm 1 is employed for the model adaption. Once having the new measurements, the algorithm uses these new measurements to adjust the model parameters $w(k)$. Through parameter adaptation, the simple model captures the nonlinear dynamics.

**Algorithm 1** Dynamic patient model Parameter Estimation

1: Inputs: $P \in R^n \leftarrow$ Inverse Correlation Matrix,
$\lambda \leftarrow$ Forgetting Factor
2: Measurement: $G(k+1), G(k), I(k)$ and $CHO(k)$
3: Estimation: $\hat{G}(k+1) = H(k)w(k)$
4: Estimation error: $e(k) = \hat{G}(k+1) - G(k+1)$
5: $\varphi = H(k) \times P$
6: Gain Factor Update: $\Gamma = \varphi/(\lambda + \varphi \times H^T)$
7: Coefficient Adaptation: $w(k+1) = w(k) + \Gamma \times e(k)$
8: Inverse Correlation Matrix Update: $P = (P - \Gamma \times \varphi)/\lambda$
9: Output: $w(k)$

## 4.4 Learning-based Model Predictive Controller

The HDT requires fusing intelligence aggregated with patient models. Fusing such knowledge with patient model and designing a MPC requires a modified approach. More recently, LB-MPC is proliferating various application domains due to their ability to model even abstract concepts within model or control actions. The LB-MPC in our approach uses the BGL measurements and patient simulator to compute the optimal insulin infusion to maintain BGL within recommended range. To compute the optimal insulin infusion, it solves a multi-time step optimization model whose objective is to reduce the BGL excursion through proper choice of insulin, and the constraints for the problem are recommended BGL limits, patient dynamics, and limits on insulin infusion

rates. The LB-MPC optimization model is,

$$
\begin{aligned}
&\min_{I(k)} \sum_{k=1}^{k+N_p} C^T I(k) + C_\gamma \gamma(k) \\
&\text{s.t.} \\
&G(k+1) = (\zeta_1(k) + \delta_a(k))G(k) + \zeta_2(k)I(k) \\
&\qquad + (\zeta_3(k) + \delta_c(k))CHO(k) + \varepsilon(k) \\
&G_{min} - \gamma(k) \leq G(k) \leq G_{max} + \gamma(k) \\
&I_{min} \leq I(k) \leq I_{max} \\
&\gamma(k) \geq 0 \quad \forall k : 1 \leq k \leq N_p
\end{aligned} \tag{5}
$$

where $\gamma(k)$ is the slack variable, which introduces a soft-constraint for modeling small variations in BGL over recommended limits. Here, $C^T$ and $C_\gamma$ denotes the cost for constraint violations, which is usually a very high value. The optimization model's output is the insulin infusion for time instants $(k+1) \ldots (k+N_p)$. In the MPC, the first among the computed insulin dosages, i.e., $k+1$ is used as the insulin dosage while the rest of the computed ones are discarded, and the procedure is repeated during the next time-instant (receding horizon approahc). The prediction horizon $N_p$ is the duration for which the control inputs are computed and $T_s$ is the sampling period for the LB-MPC. In our approach, a sampling period of 15 minutes was selected and a prediction horizon of 4 (one hour into the future) was used for most patients. The sampling period of 15 minutes was selected to capture the patient dynamics based on the physiological model.

## 4.5 Mapping macronutrient recommendations with Personalized Management

As explained earlier, E-T2D patient require complete automated insulin and food intake to be coupled. With an increase in insulin resistance, E-T2D patients behave much like T1D patients. Therefore, the management with two degrees of control: insulin infusion and nutrient modifications are recommended for the former. Whereas automated insulin infusion and macronutrient compliance are advocated for the later. In this regard, the mapping between macronutrient recommendations on personalized management and on T1D patients modelling E-T2D patients with more insulin resistance is studied. Therefore, an *in-silico* study with T1D patient dynamic model is used. Further, a diet recommender is proposed for T1D patients that could provide diet compliance.

### 4.5.1 Control algorithm for Insulin Recommendations

The MPCs' objective is to minimize the BGLs' variations from a reference set-point and without significant deviations in insulin infusion by deciding the insulin infusion to the patient. The long-term model is used to this extent was proposed by Magdelaine at al. [23]. The constraints are the physiological dynamics, limits on the insulin administration, slew-rate on the insulin infusion and the bands within which the BGL has to be maintained. We formulate the MPC design as an optimization problem given by,

$$\begin{aligned} &\min_{U} \ \mathcal{J} = (Y - Y_R)^T Q (Y - Y_R) + \Delta U^T R \Delta U \\ s.t. \quad & \qquad (6) \\ & x(k+1) = Ax(k) + Bu(k) + E \\ & y(k) = Cx(k) \\ & u_{min} \leq u(k) \leqslant u_{max} \\ & \Delta_{min} \leq \Delta u(k) \leqslant \Delta u_{max} \\ & y_{min} \leq y(k) \leq y_{max} \quad k = 1, \ldots, N_P \qquad (7) \end{aligned}$$

where $Y = [y(k+1), y(k+2).....y(k+N_P)]^T$ are predicted blood glucose concentration, $\Delta U = [\Delta u(k), \Delta u(k+1).....\Delta u(k+N_P-1)]^T$ are slew rate of the insulin administration and $Y_R = [y_R(k+1), y_R(k+2), ....., y_R(k+N_P)]^T$ are the reference trajectory or the desired glucose concentration. The MPC computes the optimal insulin infusion rates based on the current measurements on BGL which is influenced by the food intake. The MPC uses a receding horizon approach, i.e., it uses the first computed insulin infusion rate and discards the other values. In the next step, the prediction step is extended to the next time-horizon and the procedure repeats. This way MPC could correct its future inputs based on current measurements even with an approximate model. This is the feature we make use for providing implicit CHO measurements used in the diet recommender algorithm.

### 4.5.2 Diet Recommender Algorithm

In the diet recommender algorithm, we use a set of mixed meals is represented by the set $\mathcal{M} = \{m_1, m_2, \ldots, m_l\}$, where $m_i \quad \forall i \in \{1, \ldots, l\}$ represents the mixed meal. In addition, the mean, minimum and maximum values of $m_i$ are denoted by $\mu_{m_i}$, $\min_{m_i}$ and $\max_{m_i}$, respectively. Fusing this information with the long-term model and MPC, we get the implicit CHO rates of the patients' diet. To this extent, we use a stochastic framework wherein the AP computes the optimal insulin infusion using the MPC algorithm in (6). Since the physiological dynamics is very slow, we solve the

MPC for $\mu_{m_i}$, $\min_{m_i}$ and $\max_{m_i}$ CHO values and compute the insulin administration. Then we define the diet quality as

$$DQ_i = e^{-\left(\frac{\sum_k^{N_p} \|u_i(k)^* - u_i(k)_j\|}{\mu_u}\right)} \; j \in \mu_{m_i}, max_i, i \in \{1, \ldots, l\} \tag{8}$$

where $\mu_u$ and $u^*$ define the average insulin infusion rate and optimal insulin infusion rate, respectively. The above measure provides implicit measurements of CHO using patients long-term model. This way even the influences of multiple drugs or co-morbid conditions could be accommodated as well. This measure will provide the CHO measurements implicitly without having to worry about the recipe or food preparation. This DQ will then serve as a measure to recommend suitable diet for the patient.

### 4.5.3 Diet Pattern

Diet pattern also has significant influence on BGL as well. To obtain the pattern based on the implicit CHO value obtained from the recommender, we perform analysis for different feasible scenarios (continuously spaced diet or different time-spaced) on the long-term model and compute the optimal diet pattern for either the same mixed meal or for different ones which takes minimum insulin infusion while maintaining patients within the bounds.

# 5 Organization of Thesis

The outline of the thesis is as follows:

1. Chapter 1: Introduction
2. Chapter 2: Literature survey
   - Diet and its effects on diabetes.
   - Artificial pancreas
   - Patient Physiological Model
   - Control Algorithm Techniques
3. Chapter 3: Macronutrient recommendation for Remission and Progression of Diabetes in Asian Indians
   - Study Population and Sampling
   - Optimization Driven Macronutrients Recommendations
4. Chapter 4: Human Digital Twin for Personalized E-T2D Management.
   - HDT architecture.

- HDT Module Description
- Clinical trials, protocol, and data-collection for HDT.
- IoMT architecture for data collection.
- HDT models for multi-variate and multi-time step predictions.
- Explainability towards HDT.
- Structured time-series Analysis for studying inter and intra patient data.

5. Chapter 5: Personalized E-T2D Management through Smart Artificial Pancreas
   - Smart Artificial Pancreas and its schematic.
   - Adaptive E-T2D patient model from Clinical Trials.
   - LB-MPC design for personalized E-T2D management.
   - In-silico results for E-T2D management from clinical data.
6. Chapter 6: Influence of macronutrient recommendations on E-T2D Management
   - Influence of macronutrient recommendations on E-T2D patients.
   - MPC design for E-T2D patients with high Insulin resistance.
   - Diet Recommender Algorithm
   - Diet Pattern Recommendation
7. Chapter 7: Results and Discussion
8. Chapter 8: Conclusions and Future Directions.

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# 6 Publications

1. Human Digital Twin for Personalized Elderly Type 2 Diabetes Management
   **Padmapritha Thamotharan**, Seshadhri Srinivasan, Jothydev Kesavadev, Gopika Krishnan, Viswanathan Mohan, Subathra Seshadhri, Korkut Bekiroglu, and Chiara Toffanin, *Jounal of Clinical Medicine*, **6**, 6 (2023)

2. Macronutrient Recommendations for Remission and Prevention of Diabetes in Asisn Indians Based on Data-Driven Optimization Model: The ICMR-INDIAB National Study
   Anjana, R.M., Srinivasan, S., Sudha, V., Joshi, S.R., Saboo, B., Tandon, N., Das, A.K., Jabbar, P.K., Madhu, S.V., Gupta, A., Bajaj, S.,Chowdhury S., Kalra S., Gayathri R., Abirami K., Manasa V.S., **Padmapritha. T**, Lakshmipriya. N., Geetha. G., Deepa. M., Prdeepa. R., Ranjith unnikrishnan, Anura viswanathan, Kamala Krishnaswamy, Kaur T., Rupender singh, and Vishwanathan Mohan
   *Diabetes Care*, **45**, 12, 2883–2891 (2022).

3. Smart Artificial Pancreas with Diet Recommender System for Elderly Diabetes
   **T. Padmapritha**, B. Subathra, Munnevver Mine Ozyetkin, Seshadhri Srinivasan, Korkut Bekirogulu, Jothydev Kesavadev, Gopika Krishnan, Geethu Sanal
   *IFAC Papers OnLine*, **53**, 2, 16366-16371 (2020)